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Providing Proactive Scaffolding During Tutorial Dialogue Using Guidance from Student Model Predictions

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Abstract. This paper discusses how a dialogue-based tutoring system makes decisions to proactively scaffold students during conceptual discussions about physics. The tutor uses a student model to predict the likelihood that the student will answer the next question in a dialogue script correctly. Based on these predictions, the tutor will, step by step, choose the granularity at which the next step in the dialogue is discussed. The tutor attempts to pursue the discussion at the highest possible level, with the goal of helping the student achieve mastery, but with the constraint that the questions it asks are within the student's ability to answer when appropriately supported; that is, the tutor aims to stay within its estimate of the student's zone of proximal development for the targeted concepts. The scaffolding provided by the tutor is further adapted by adjusting the way the questions are expressed.

Keywords: Dialogue-based tutoring systems, Scaffolding, Student Modeling, Zone of Proximal Development.

1 Introduction

Tutorial dialogue systems typically implement a framework called "Knowledge Construction Dialogues" (KCDs), which guide all students through the same pre-scripted "directed line of reasoning" [10], regardless of the student's ability level. KCDs only deviate from the main path in the script to issue "remedial sub-dialogues" when the student answers incorrectly, then pop back up to the main path (e.g., [3, 9]). This approach can be frustrating and inefficient for some students because they are forced to go through long, repetitive and unnecessary discussions due to the dialogues' lack of adaptation to students' knowledge level.

One possible way to overcome this limitation is to incorporate a student model in the tutorial dialogue system that would emulate how human tutors construct and dynamically update a normative mental representation of students' grasp of the domain

content and use this representation to adapt the tutor's scaffolding to meet students' needs [5].

Additionally, a tutorial dialogue system needs policies for how to adaptively structure a discussion. Research on human tutoring (e.g., [17]) shows that tutors use their assessment of student ability to target scaffolding to the student's "zone of proximal development" (ZPD) [15] —"a zone within which a child can accomplish with help what he can later accomplish alone" [2]. This work suggests that automated tutors should ask challenging questions which the student can answer with adequate support and, eventually, be able to answer without assistance. The tutoring system described herein implements a decision-making process that attempts to emulate this aspect of human tutoring with the support of a student model.

2 The Adaptive Tutoring System: Rimac

Rimac is a dialogue-based tutoring system that engages high school students in conceptual discussions after they solve quantitative physics problems (e.g., [1,13]). When using the tutor, students typically start by taking an online pretest; they then solve problems on paper, such as the one presented in Fig. 1. After working on a problem, students use the tutor to watch a video of a sample correct solution and then engage in several reflective dialogues, which focus on the concepts associated with the quantitative problem. An example of a reflection question is shown in Fig. 1.

Homework problem statement: Suppose you aim a bow horizontally, directly at the center of a target 25m away from you. If the speed of the arrow is 60 m/s, how far from the center of the target will it strike the target? That is, find the vertical displacement of the arrow while it is in flight. Assume there is no air friction.

Reflection Question: During the arrow's flight, how does its horizontal velocity change?

Fig. 1. A sample homework problem statement and reflection question

Rimac's reflective dialogues were designed so that the tutor could provide domain and instructional contingency [16] depending on the student's level of performance. To achieve domain contingency—that is, to decide what content to address next—different versions of the dialogues were developed, each corresponding to a line of reasoning (LOR) at different levels of granularity. These LORs, when embedded in dialogues, can be visualized as a directed graph, where nodes are concepts that the tutor queries the student about and arrows are the inferences needed to go from one node to the next. (See Fig. 2 for a sample segment of a discussion about the reflection question shown in Fig. 1. P0 → P1 would represent an expert LOR and P0 → S1 → S2 → P1 a LOR with intermediate reasoning steps.) The system captures such inferences as knowledge components (KCs) which will be used to predict if the student can answer the next question correctly. To implement instructional contingency—that is, to vary the way tutor questions are expressed—authoring rules were developed to guide how much support to

embed in a question. For example, node S1 in Fig. 2 can be expressed directly as, "What is the value of the acceleration in the horizontal direction?" or with more support as, "Given that the horizontal net force on the arrow is zero, what is the horizontal acceleration of the arrow?" (see [12] for a detailed description of these authoring rules).

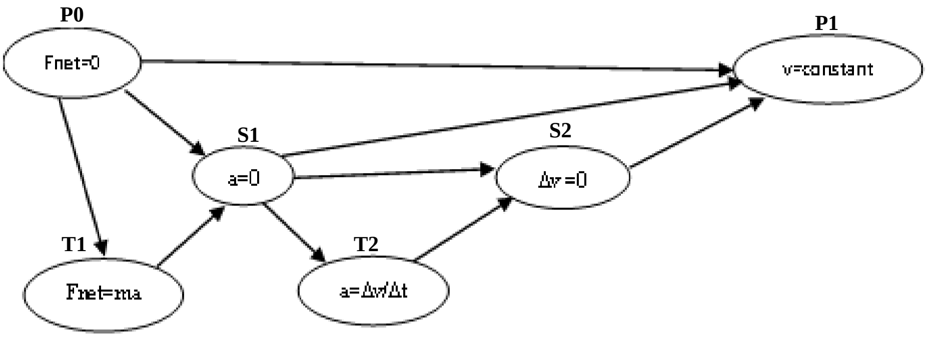

Fig. 2. Graphical representation of the line of reasoning Fnet=0 → v=constant with different levels of granularity. Nodes represent questions the tutor could ask. Arcs represent the knowledge (KCs) required to make the inference from one node to the next.

Rimac incorporates a student model which enables it to predict the likelihood of a student answering a question correctly [6, 7]. An individual student model is built in two steps: first, using the results of the student's pretest, a clustering algorithm classifies the student as low, medium, or high. Second, the student is assigned a cluster-specific regression equation that is then personalized with the results of the student's pretest. The regression equation assigned to the student represents an implementation of an Instructional Factor Analysis Model (IFM), as proposed by [4]. This student model uses logistic regression to predict the probability of a student answering a question correctly as a linear function of the student's proficiency in the relevant KCs. Additionally, as the student progresses through the dialogues, his student model is dynamically updated according to the correctness of his responses to the tutor's questions.

Once the tutor engages the student in a reflection dialogue, it needs to decide at what level of granularity it will ask the next question in the LOR (or in a remediation if the previous question was answered incorrectly), to proactively adapt to the student's changing knowledge level. The tutor will always aim for mastery by selecting the question at the highest possible level that the student can likely answer correctly with adequate support. In other words, the tutor will choose a question in the highest possible LOR that it deems the student will respond correctly or that it perceives to be in the student's ZPD. To make this choice, Rimac consults the student model which predicts the likelihood that the student will answer a question correctly. The tutor interprets this probability as follows: if the probability of the student responding correctly is higher than 60% then the student is likely to be able to respond correctly, and if it is lower than 40% the student is likely to be unable to respond correctly. However, as the prediction gets closer to 50%, there is greater uncertainty since there is a 50% chance that he will be able to answer correctly and a 50% chance that he will not be able. This uncertainty

on the part of the tutor about the student's ability could be indicative that the student is in his ZPD with regards to the relevant knowledge. Hence the tutor perceives the range of probabilities between 40% and 60% as a model of the student's ZPD [6,7]. Thus, the tutor will choose to ask the question in the highest possible LOR that has a predicted probability of at least 40% of being answered correctly. The expression of the question within the LOR is adapted to provide increased support as the certainty of a correct answer decreases [12].

As an example of how the tutor proactively adapts its scaffolding during a dialogue, suppose the student has correctly answered the question at node S1 in Fig. 2. The tutor will consult the student model to estimate the likelihood that the student would be able to answer P1 (the highest possible node in the LOR) correctly. If this estimate is at or above 40% it will ask the corresponding question because this would indicate that the student is at or above the tutor's model of the student's ZPD for that question. However, if the probability is below 40% the tutor will try to pursue the discussion in a simpler way and examine S2 in the same manner as with P1. This process is repeated until a question can be asked or a leaf is reached in which case the question is asked at the highest level of support. As described previously, the tutor further adapts the support it provides by adapting how the question at the selected node is expressed.

3 Discussion and Future Work

In this paper we described a tutoring system, Rimac, that strives to enhance students' understanding of physics concepts and their ability to reason through "deep reasoning questions" [8]. Rimac presents a novel approach to the use of a student model by incorporating the idea of modeling the tutor's estimate of the student's zone of proximal development which it then uses to guide scaffolding during reflective tutorial dialogues. The system takes a proactive approach by anticipating students' needs and presenting a question at each step of a LOR that challenges the learner without overwhelming him, and by expressing the question with adequate support.

The tutor's scaffolding adheres to the main tenets of contingency, fading, and transfer of responsibility [14]. This is accomplished by proactively varying the level of complexity of the knowledge discussed and the way it is expressed and by adapting, step by step, to the student's changing ability. The tutor reduces the support it provides (i.e., it fades) as the learner becomes more competent and gradually provides the intermediate steps on his or her own (transfer of responsibility).

An evaluation of the effectiveness of the tutoring system is currently being conducted. The version of Rimac described herein is being compared with a control version that embeds a poor-man's student model which assigns students to a fixed LOR level in each reflection dialogue based solely on their pretest scores [11].

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